

THE CULTURAL EXPRESSION SIGNATURE FRAMEWORK

*The Current Largest Unaddressed Asymmetry in Synthetic Media
Detection,
Identity Verification, and Human-Facing AI Deployment*

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Executive Summary

This paper identifies and formally describes a human perceptual capacity that, despite operating reliably across billions of daily interactions, has not been named, modeled, or applied as a structured tool in any field that depends on it.

Humans can detect, from a single photograph and in under one second, that a person does not belong to their own regional or cultural reference population. This is not a conscious analytical judgment. It is a pre-conscious, automatic, exclusion-only signal — a template-violation response generated by decades of immersive socialization. The observer does not identify where the person is from. They know instantly that the person is not from here.

This capacity — here formally named the Cultural Expression Signature (CES) — is universal across all human populations, operates identically regardless of the observer's or subject's gender, applies to any still image regardless of context or topic, is strongest where phenotypic similarity between populations is greatest, and is entirely socialization-derived rather than genetic.

The framework simultaneously identifies an unmodeled detection gap in four major applied domains that have not yet adapted to its existence:

- (1.) Deepfake and synthetic media detection**, where technically sophisticated fakes pass all current automated detectors but fail the CES test instantly for culturally calibrated human observers;
- (2.) AI-generated film, video, and prompt-to-media production**, where generated performances default to a culturally unanchored global mean expression signature;

(3.) Avatar and simulation systems — from games to metaverse platforms to social VR — where photorealistic rendering addresses the wrong realism layer;

(4.) Embodied AI and physical humanoid robotics — from domestic assistants to service robots to companion systems — where cultural expression authenticity is absent from every current development roadmap.

The cross-domain synthesis is the core contribution. Each field has encountered the symptom. None has named the cause. This paper provides the unified diagnostic framework.

Disclaimer and Scope

This framework concerns learned cultural expression — not race, ethnicity, religion, national origin, or any inherited biological characteristic. It makes no claims about genetic determinism of any kind and positions no population as a norm, default, or reference standard.

The Cultural Expression Signature framework proposes that humans acquire population-specific patterns of facial muscle use, emotional performance style, and contextual coherence through decades of immersive socialization within a specific cultural environment. This is a learned phenomenon, operating through the same mechanisms by which people acquire accents, humor conventions, and social norms.

This framework applies equally and without hierarchy to all human populations. A Brazilian observer demonstrates the same exclusion capacity regarding Brazilian expression norms as a Japanese observer demonstrates regarding Japanese norms. The mechanism is universal. No population is privileged or primary. The framework describes a human universal, not a property of any particular group.

What this framework IS:

- A model of culturally acquired expression behavior that operates below conscious awareness
- An observational framework applicable to OSINT methodology, deepfake detection, simulation realism, and embodied AI development
- A description of how immersive socialization produces measurable, consistent behavioral output readable from static images

- A neutral analytical tool applicable across all human populations without exception

What this framework is NOT:

- A theory of racial difference or racial hierarchy
- A claim about biological, genetic, or inherited characteristics
- A profiling tool based on appearance, phenotype, or physical features
- A framework for predicting individual behavior from group membership
- A tool for discrimination, exclusion, surveillance targeting, or any form of prejudice
- Gender-specific — the exclusion capacity applies to all observers regardless of gender when evaluating any presented subject

The framework explicitly recognizes that cultural expression signatures are acquired, not inherited. A person of any ancestry raised in a different cultural environment will develop the expression signature of that environment. The signal follows socialization, not bloodline. Phenotype is analytically irrelevant to the framework's core claims.

Furthermore, the framework describes population-level statistical tendencies, not individual determinism. Every population contains the full range of individual variation. No individual can be assessed, classified, or judged on the basis of population-level expression norms. The framework has no valid individual-level application and must not be used as one.

Any application of this framework for purposes of discrimination, harassment, surveillance targeting, or prejudice of any kind falls entirely outside its scope and intent and is explicitly rejected.

1. Introduction: The Asymmetry

Humans can instantly detect 'not my region/culture' from a single photograph — a pre-conscious, automatic, exclusion-only capacity operating below analytical awareness, present in all populations, running on every topic and context without exception, and constituting an unmodeled detection layer with direct implications for deepfake forensics, avatar realism, OSINT identity verification, and every domain building human-facing AI systems.

This paper identifies what may be the current largest unaddressed asymmetry across four major technology and security domains: a human perceptual capacity that operates reliably across billions of daily interactions while remaining entirely unmodeled by every technical system that depends on it.

In signal detection terms, an asymmetry of operational significance exists when one party possesses a capability that another party neither possesses nor has formally identified as a capability worth acquiring. The CES asymmetry is unusual in scale: it is not a gap between two opposing actors but between human perceptual capacity and an entire technology industry simultaneously. Billions of dollars flow into systems that would perform fundamentally better if they incorporated a human capacity that researchers have not formally named.

Individual components of what follows have partial precedents scattered across disconnected fields. Ekman and Friesen established cross-cultural variation in emotional expression display rules in the 1960s and 1970s [1][2]. Elfenbein and Ambady documented the in-group advantage in emotion recognition across a meta-analysis of 97 studies [3]. Marsh, Elfenbein, and Ambady identified nonverbal 'accents' in facial expressions that allow observers to identify cultural background from photographs [4]. Dailey et al. demonstrated computationally that culture-specific expression dialects emerge from environment-specific training data [5].

What has not existed before is the integration — the recognition that a single unmodeled human capacity simultaneously creates a detection gap in deepfake forensics, a realism ceiling in avatar and simulation systems, an untapped signal channel in OSINT and identity verification, and a measurable developmental blind spot across all embodied AI and robotics. The cross-domain synthesis is the contribution. Each field has encountered the symptom. None has named the cause.

2. The Cultural Expression Signature: Core Framework

2.1 Definition

A Cultural Expression Signature (CES) is the integrated, multi-channel pattern of culturally acquired expression behavior that characterizes a specific regional or national population and is readable from static photographic imagery by observers sufficiently immersed in the same reference population.

The CES is not a single feature. It is a bundle operating simultaneously across multiple channels that the observer integrates pre-consciously into a single coherent assessment.

2.2 The Three-Layer Model

Layer 1: Environmental Coherence

Architecture, objects, electrical fixtures, vehicles, street furniture, product packaging, interior design conventions. Any single channel can trigger the exclusion signal independently. An observer does not consciously think 'that electrical cabinet is non-local.' The violation fires automatically and is reported. Environmental coherence is the outermost and most cognitively accessible layer — it is what observers most readily verbalize when asked to explain their judgment.

Layer 2: Performed Identity

Makeup era and style conventions, clothing cut and fabric choices, body language defaults, postural norms, relationship with the camera in self-presented imagery. This layer is culturally calibrated and regionally specific even in formats that appear universal. A professional headshot, a social media profile photograph, a LinkedIn portrait — each involves culturally specific conventions for what constitutes appropriate professional or social self-presentation. The conventions differ dramatically at the expression execution level across populations.

Layer 3: Expression Micro-Execution

The deepest and most operationally significant layer. The specific muscle recruitment pattern for each emotional state — how pensiveness, amusement, excitement, distraction, and neutrality are physically constructed in that population. Not what emotion is displayed but how it is built. This is not a property of formal or performative contexts. It runs continuously on every topic, in every situation, whether the subject is discussing their car, their spouse, their job, or their opinion about a sporting event. It is present and readable in unguarded candid images, in professional headshots, in video frames, and in social media posts across all categories of content.

Critically, Layer 3 is most purely visible precisely when the person is least performing. When the only layer running is deep socialization, the CES signal is at maximum clarity. This is what distinguishes the framework from conventional cross-cultural business communication literature, which documents conscious behavioral norms. The CES operates below conscious awareness and cannot be switched off by the subject.

2.3 The Asymmetric Exclusion Principle

The CES mechanism does not produce positive identification. It produces reliable exclusion. The observer does not determine where the person is from — they determine with high confidence that the person is not from their own reference population.

In signal detection terms this produces high sensitivity and low specificity: near-zero false negatives on 'not from my population' combined with poor accuracy on positive placement. The mechanism fires reliably, quickly, and involuntarily. It degrades sharply outside the observer's reference population — an observer calibrated to one regional population has no calibrated template for distinguishing between two foreign populations phenotypically similar to each other.

The exclusion signal is strongest where phenotypic distance between the subject and observer's reference population is smallest. Where two populations share phenotype — same skin tone range, same hair color distribution, same general facial structure — phenotype contributes almost nothing to the discrimination task. The entire discriminative load falls on the expression layer, which the brain has accordingly developed extraordinary sensitivity to. The CES mechanism is therefore inversely proportional to phenotypic distance: maximum sensitivity occurs at minimum phenotypic distance.

This is the mechanism's most counterintuitive property and its most theoretically significant one. Populations that look most alike to outside observers have developed the finest mutual exclusion capacity between themselves.

2.4 The Socialization Proof: Natural Experiments

Two natural experiments establish that the CES is entirely socialization-derived and phenotype-independent.

First: populations sharing common colonial genetic heritage across centuries of geographic separation. The founding population of New Amsterdam — present-day New York — was substantially Dutch. The Dutch colonial heritage of the American Northeast is genetically traceable and historically documented. Today, an individual of identical Dutch genetic lineage, one socialized in the Netherlands and one in the United States, will produce entirely different cultural expression signatures, detectable from a single photograph in under one second by calibrated observers from either reference population. The genetic raw material is shared. The expression output is not.

Second: multigenerational emigrant communities. Families of any national origin that relocate and raise subsequent generations in a new cultural environment progressively shift their expression signature toward the dominant socialization environment. By the third or fourth generation the original signature is effectively absent — replaced not by a hybrid but by the locally acquired one. The first generation retains the signature of origin. The second shows partial convergence. By the third the origin signature has been overwritten. This generational gradient is a direct, observable prediction of the CES framework: the expression signature follows socialization duration, not ancestry.

These two cases establish the same conclusion from different directions: the signal follows the cultural environment, not the bloodline.

2.5 Speed and Pre-Consciousness

The sub-second detection speed is the property that places the CES mechanism below conscious processing. A person cannot consciously analyze periorbital muscle tone, emotional amplitude register, resting face construction, and gaze behavior simultaneously in under one second. What fires in under one second is a template-violation signal — the implicit statistical model built from decades of immersive exposure detecting deviation before any conscious process engages.

This places the CES detection mechanism in the same architectural category as native speaker accent detection (foreignness detected before a word is complete), own-race face recognition advantage (processing differences measurable at millisecond level in neuroimaging), and domain expert pattern recognition (the chess grandmaster identifying the wrong move before conscious analysis). All share the same structure: dense implicit statistical model built through immersive exposure, producing deviation signals that precede and bypass deliberate analysis.

The mechanism fires in people who have never consciously considered cross-cultural expression differences, who have never traveled internationally, and who cannot articulate what they saw. It fires from a single still photograph with no audio, no motion, no context, no environmental cues — just a face. That is the single-photograph condition that provides the cleanest isolation of the CES signal from all alternative explanations.

3. Literature Context and the Novelty Claim

3.1 What the Existing Literature Established

The scientific literature on cross-cultural facial expression has established a coherent and well-replicated foundation. Darwin proposed the universality of basic emotional expression in 1872 [6]. Ekman and Friesen's cross-cultural studies from the late 1960s onward demonstrated that six basic emotions were recognizable across cultures at above-chance levels [1][2][7]. This became the dominant paradigm — the universality hypothesis.

Subsequent research established that universality coexists with systematic cultural variation. Elfenbein and Ambady's 2002 meta-analysis of 97 studies found that recognition accuracy was reliably higher when encoder and decoder were from the same cultural group — the in-group advantage [3]. Their dialect theory proposed that emotional expression functions like a universal language

with regional accents [8]. Marsh, Elfenbein, and Ambady demonstrated in 2003 that observers could identify the cultural background of expressors from photographs at above-chance levels — including when muscle movements were standardized to eliminate physical differences, leaving only the expression execution as the discriminative variable [4]. Dailey et al. showed computationally that culture-specific expression classifiers emerge naturally from culture-specific training environments [5]. Li et al.'s 2025 systematic review formalized a two-stage model of cross-cultural emotion perception incorporating both perceptual and social-cognitive processing [9].

This body of work is substantial, well-replicated, and provides the scientific foundation on which the CES framework builds.

3.2 What the Existing Literature Did Not Do

Despite this foundation, the existing literature has four critical gaps that the CES framework addresses.

First: the existing research measures positive identification accuracy. Studies present observers with stimuli and ask them to categorize, recognize, or identify. The CES framework's core claim is about exclusion — a capacity that is stronger, faster, more reliable, and more practically significant than positive identification but has not been the primary dependent variable in any major study.

Second: existing studies use controlled laboratory stimuli — posed expressions, standardized photographs, actor databases. The CES exclusion capacity operates on ordinary photographs across all content categories including unguarded candid images, social media photographs, professional headshots, and video frames. The ecological validity gap between laboratory paradigms and real-world CES operation is substantial.

Third: no prior work has proposed the inverse phenotypic distance relationship — that the CES mechanism is strongest precisely where populations are most phenotypically similar, because in those cases phenotype is uninformative and the expression layer carries the full discriminative load.

Fourth and most significantly: no prior work has connected the cross-cultural expression literature to its applied implications across deepfake detection, avatar realism, OSINT methodology, and embodied AI development. These four domains have been treated as entirely separate problems with separate literatures. The CES framework identifies them as four expressions of one unrecognized phenomenon.

3.3 The Novelty Claim

The novelty of this framework lies in three areas: the formal naming and characterization of the exclusion asymmetry as distinct from the identification

capacity documented in prior literature; the inverse phenotypic distance relationship as a testable theoretical prediction; and the cross-domain synthesis connecting a single unmodeled perceptual mechanism to four major applied fields simultaneously. The individual components are grounded in existing science. The integration is new.

4. Applied Domains: Where the Gap Lives

4.1 Deepfake and Synthetic Media Detection

Current deepfake detection operates at the technical artifact layer — blending seams at face boundaries, temporal inconsistency in video, GAN fingerprints in frequency domain analysis, physiological signal absence [10][11][12]. This approach has produced progressively more sophisticated detectors. It has not produced adequate ones. Real-world benchmark evaluation shows that even leading commercial detectors achieve approximately 78% accuracy against contemporary in-the-wild deepfakes, while top automated systems still fall short of the approximately 90% accuracy estimated for human forensic analysts [13]. The gap between human and machine performance has persisted despite years of investment in technical detection methods.

The CES framework proposes a specific explanation for part of this gap that the technical detection literature has not addressed: human forensic analysts are reading a cultural expression authenticity layer that technical detectors do not model.

Deepfake generation pipelines — whether GAN-based, diffusion-based, or face-swap architectures — are trained on globally aggregated data. The models learn average human facial muscle movement and statistically dominant expression patterns, producing what is here termed the global mean face performance: an expression output that is statistically plausible as human but belongs to no specific cultural population authentically. It is Western-internet-overrepresented and increasingly homogenized by platform aesthetic norms.

A technically perfect deepfake of a claimed regional identity will fail the CES test for any observer calibrated to that regional population. The emotional amplitude range will be wrong. The muscle recruitment pattern for each emotional state will default to global mean rather than population-specific execution. The professional headshot will perform warmth in the wrong register. The casual social media image will carry the wrong relationship with the camera. The deepfake will pass every artifact detector and fail instantly for every culturally calibrated human observer from the claimed population.

This failure mode is architectural, not parametric. Closing the gap would require regionally segmented expression training data labeled at population level — a knowledge base that does not currently exist in usable form because the academic taxonomy required to produce it has not been built. The gap is therefore not a tunable parameter. It is a structural limitation of current generation methodology that will persist until the CES framework or something equivalent provides the theoretical foundation for a solution.

4.2 OSINT and Identity Verification

Open source intelligence methodology has developed sophisticated technical tooling: reverse image search, metadata extraction, geolocation from environmental cues, cross-platform identity correlation. The CES framework adds a signal channel that is currently informal, unstructured, and operationally underutilized.

Culturally calibrated observers in online communities demonstrate spontaneous, unsolicited, convergent nationality exclusion behavior. When presented with a profile image or video that fails the CES test for a claimed regional identity, observers from that reference population self-report the violation without prompting, in their own language, using geographic and social rather than aesthetic framing: 'not from here,' 'wrong,' 'doesn't fit.' This behavior occurs independently across multiple observers without coordination.

The operational significance of this behavioral pattern is that it constitutes free distributed annotation. Comment sections, forum threads, and platform discussion become an involuntary tagging system in which fabricated or mislabeled identities receive convergent CES rejection signals from independent observers. Convergence without coordination is a strong signal. A single observer flagging a profile may be noise. Ten independent observers from the same reference population flagging the same profile without communicating are a meaningful signal.

Critically, the signal extends beyond the face to all CES layers simultaneously. Environmental coherence failures — wrong vehicle type, wrong electrical infrastructure, wrong architectural period, wrong interior design conventions — trigger the same exclusion response through Layer 1 independently of any facial signal. A fabricated identity must achieve CES coherence across all layers simultaneously to pass inspection by a calibrated observer community. Current fabrication methodology addresses none of these layers deliberately.

The OSINT implication is direct: systematic collection and cross-referencing of spontaneous CES rejection behavior from platform comment data constitutes a new signal class for identity verification that no current methodology formalizes.

4.3 Avatar and Simulation Realism

The dominant framework in avatar and simulation realism research is the uncanny valley — Mori's 1970 observation that near-human appearance produces rejection rather than acceptance in human observers [14]. Research and development in this space has focused heavily on photorealism: closing the gap in geometry, skin rendering, hair physics, and movement dynamics. Significant progress has been made on this axis.

The CES framework identifies a separate realism ceiling that sits entirely below the photorealism threshold and has not been formally described. An avatar can clear the photorealism threshold entirely — achieving technically indistinguishable human appearance — and still fail CES calibration, producing a face that is technically perfect but emotionally readable as belonging to no specific population. This failure mode is phenomenologically distinct from the AI uncanny valley response. The uncanny valley produces active discomfort: something feels wrong, the face disturbs. The CES failure produces a quiet certain recognition of non-belonging: not disturbing, simply definitively not from here.

The distinction between these two failure modes is practically significant for development. A team that has solved the technical uncanny valley and is still receiving rejection signals from regional user populations has no diagnostic framework for what is failing unless the CES layer has been formally identified. They will continue iterating on geometry and rendering — the wrong variables — because the actual failure is in the expression signature layer that no current development methodology addresses.

This applies across the full avatar deployment spectrum: social VR and metaverse platforms building toward photorealistic self-representation, gaming environments with culturally specified characters, professional virtual presence tools, and AI companion systems. The entire avatar industry is optimizing for the wrong realism layer while the CES ceiling remains unaddressed on every roadmap.

4.4 Embodied AI and Physical Humanoid Robotics

The embodied deployment context extends the CES problem to its most consequential expression. Physical humanoid robots — currently being deployed in service, hospitality, healthcare, domestic assistant, and companionship roles — face the same CES failure mode in physical form, with higher stakes.

A service robot deployed in a specific regional market that has been optimized for movement physics, speech naturalness, and facial geometry but not cultural expression authenticity will produce the CES exclusion response in every culturally calibrated user it interacts with. The robot will look right, move right, and speak right. It will feel persistently like a stranger. Users will not be able to

articulate why. The development team will have no diagnostic framework for the failure without the CES framework.

For domestic and companion robots — designed for intimate long-term co-habitation — CES failure is the most consequential possible outcome. The entire value proposition of an intimate companion is presence and belonging. A technically perfect physical form with a culturally unanchored expression system fails this proposition at its foundation. The face is right. The person — the felt cultural presence — is absent.

No current development methodology in embodied robotics includes cultural expression authenticity as a design variable. It does not appear on any published robotics development roadmap. The problem has not been identified as a problem — which is precisely the condition that defines a significant unaddressed asymmetry.

The cascade across these four domains maps onto a progression of deployment intimacy and stakes: games (entertainment, lowest stakes), deepfakes (forensic and security), AI film (cultural production at scale), avatars (daily social presence), domestic assistants (household co-habitation), companions and sex robots (intimate relationship). At every level the same failure mode is active. At every level the stakes increase as the interaction becomes more intimate.

5. Significance and Novelty

5.1 What Changes With This Framework

Before this framework: the human capacity to exclude 'not from my population' from a single photograph is an informal, unstructured folk observation. Every person with sufficient socialization depth exercises it daily without naming it. No field that depends on it has formalized it. The deepfake detection community does not model it. The avatar development community does not design for it. The OSINT community does not systematically exploit it.

After this framework: the capacity has a name, a three-layer structure, a theoretical mechanism, a testable prediction (the inverse phenotypic distance relationship), a set of empirical implications across four domains, and a formal connection to the existing cross-cultural expression literature that grounds it in peer-reviewed science.

Naming is not a trivial contribution. A phenomenon that cannot be named cannot be systematically studied, taught, operationalized, or designed against. The CES

framework converts an informal human intuition into a structured technical and scientific concept for the first time.

5.2 The Timing Argument

The framework arrives at a specific moment in the technology development trajectory of all four affected domains. Deepfake generation quality is improving rapidly; technically perfect fakes are becoming increasingly accessible. Avatar photorealism is approaching indistinguishability in controlled conditions. Physical robotics is moving from industrial to social deployment. AI companion systems are being deployed commercially.

In each domain, technical execution has advanced far enough to be approaching the threshold at which CES failure becomes the dominant remaining problem — but has not yet fully crossed it. The technical uncanny valley is still providing partial cover for the CES failure mode: when a face has rendering artifacts, observers reject it for technical reasons without reaching the CES layer. As technical execution improves and rendering artifacts are eliminated, the CES layer is exposed in isolation. The better the technology gets, the more visible the CES failure becomes.

The framework is being published one step ahead of where the affected fields are about to arrive. That is the optimal timing for a foundational framework: establishing priority before the problem it describes becomes universally visible.

5.3 The Asymmetry Does Not Close on Publication

Publishing the framework makes the gap visible to all parties simultaneously — researchers, developers, defenders, and adversarial actors. However, the operational asymmetry does not immediately close. Human CES capacity is already deployed and requires no infrastructure investment to exploit as a detection tool. Closing the gap from the synthesis side — building deepfake generators, avatars, and robots that achieve genuine CES authenticity — requires foundational infrastructure that does not yet exist: regionally segmented expression training data, population-specific emotional amplitude taxonomies, cultural expression signature databases labeled at the required granularity. This work has not started because the problem has not been identified. The lead time for the defensive application of the framework is therefore substantially shorter than for adversarial adaptation.

6. Ethics and Privacy

The ethical considerations of this framework require explicit treatment given the sensitivity of any research touching on human social categorization.

6.1 The Socialization Basis Is Non-Negotiable

The framework is built on a specific empirical claim: the CES is acquired through socialization and is not a property of genetics, ancestry, phenotype, or any inherited characteristic. This is not a diplomatic hedge. It is a strong empirical prediction supported by the natural experiments described in Section 2.4 and by the existing cross-cultural expression literature. Any application of the framework that treats CES signals as proxies for genetic, ethnic, or racial categories is scientifically incorrect in addition to being ethically unacceptable.

6.2 Individual-Level Application Is Explicitly Excluded

The framework describes population-level statistical tendencies. Individual variation within any population spans the full range of the framework's variables. The CES exclusion signal fires on deviation from a population mean — it does not characterize any individual. No individual can be validly assessed, profiled, or categorized on the basis of CES-derived inferences. Any such application would be both scientifically invalid and ethically impermissible.

6.3 Intended Applications

The framework's intended applications are analytical and technical: improving the fidelity of synthetic media detection systems, informing avatar and simulation design, enhancing OSINT methodology for identity verification of fabricated profiles, and advancing the realism of embodied AI systems. These are legitimate research and development objectives.

6.4 Misuse Scenarios and Rejection

The author explicitly anticipates and rejects the following misuse scenarios: use of CES methodology to target, surveil, or discriminate against individuals on the basis of inferred cultural background; deployment of CES-derived tools for immigration enforcement, racial profiling, or any form of population control; commercial exploitation of CES signals for manipulative targeting in advertising or political influence operations. These applications fall outside the framework's scope, contradict its ethical foundations, and are explicitly disavowed.

6.5 Privacy in Distributed Observer Methodology

The OSINT application described in Section 4.2 relies on publicly observable comment behavior in open digital spaces. No methodology is proposed that involves accessing private communications, aggregating personal data, or creating individual profiles from CES signals. The signal of interest is the convergent public behavior of observer communities, not the attributes of any individual subject.

7. Conclusion

This paper has introduced the Cultural Expression Signature framework — a formal description of a human perceptual capacity that has operated across all human populations throughout recorded history without being named, modeled, or applied as a structured tool in any field that depends on it.

The capacity is simple to state: humans can detect, from a single photograph and in under one second, that a person does not belong to their own regional or cultural reference population. The mechanism is pre-conscious template-violation. The signal is exclusion, not identification. The capacity is universal, socialization-derived, gender-independent, and strongest where phenotypic similarity between populations is greatest.

The implications are not simple. Four major applied domains — deepfake and synthetic media detection, OSINT and identity verification, avatar and simulation realism, and embodied AI and physical humanoid robotics — are each operating with a structural blind spot that the CES framework resolves. Every technical advance in each of these domains increases the practical importance of the framework, because as technical execution improves the CES layer becomes the dominant remaining failure mode.

The cross-domain synthesis is the core contribution. The literature had the pieces. This framework provides the map.

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